Evaluation of methods for scheduling clinic appointments in surgical service: a statecharts-based simulation study

Boris G. Sobolev[1], PhD, Victor Sanchez[2], MSc and Lisa Kuramoto[2], MSc
[1]*School of Population and Public Health, The University of British Columbia*
[2]*Centre for Clinical Epidemiology and Evaluation, Vancouver Coastal Health Research Institute*
Vancouver, Canada

1. Introduction

The management of outpatient consultations constitutes an important aspect of planning activities in surgical services (Vissers, 1979). The scheduling process used for clinic appointments determines the appointment date for any patient referred for consultation about an operation (Jun et al., 1999). Within a regional network of hospitals, a variety of methods may be used for scheduling surgical consultations, but a better understanding is needed of the implications of these different methods for access to elective surgery (Naylor, 1991).

Walshe and Rundall have argued that the paradigm of evidence-based medicine should be applied to health care management so that decisions about organizing, structuring, and delivering health services are based on practices that are known to be effective (Walshe & Rundall, 2001). Increasingly, health services research seeks to evaluate proposed changes in health systems. When feasible, intervention studies are used to compare existing and proposed approaches to management and policy (Ham et al., 2003). However, when organizational interventions are not feasible for ethical, economic, or other reasons, computer simulation provides an alternative method of quantifying the effects of proposed changes in the organization and management of health care delivery (Fone et al., 2003).

Previous studies have used analytical and simulation models to explore in detail the scheduling of appointments for outpatient services, and a comprehensive review of this literature has been published elsewhere (Cayirli & Veral, 2003). Applications of the simulation approach have included assessing the impact of alternative appointment schedules on waiting times in a specialty department (Harper & Gamlin, 2003), examining the capacity needed to reduce access times in outpatient departments (Elkhuizen et al., 2007), evaluating scheduling rules in terms of physicians' idle time when the type of patient requesting an appointment at a later time is unknown (Klassen & Rohleder, 1996; Klassen & Rohleder, 2004), comparing appointment systems for patients with different needs in a multifacility internal medicine department (Wijewickrama & Takakuwa, 2008), and assessing the impact of operating conditions on the performance of rules for scheduling appointments (Ho & Lau, 1999). Other authors have described the use of computer simulation to support decision-making in outpatient clinics (Erdem et al., 2002), to improve utilization of resources, and to reduce physicians' overtime (Westeneng, 2007).

Other investigators have established that the length of time a patient has to wait between referral and consultation depends not only on the method for scheduling appointments and the number and type of referrals, but also on the availability of surgeons for appointments, as these physicians may have administrative, educational, or research commitments in addition to their clinical practices (Harper & Gamlin, 2003; Meredith et al., 1999). Our previous analysis suggested that the clinic appointment system may influence the time between consultation and surgery; for example, pooling referrals, i.e., placing all patients on one appointment list and scheduling appointments with the first available surgeon, seemed to reduce the time to consultation but increased the time to surgery for patients with non-urgent needs (Vasilakis et al., 2007).

In surgical services where patients may see any one of a group of surgeons, directing patients to the shortest queue has long been considered a suitable alternative to the single-queue system of appointments (Edwards et al., 1994). Both of these systems differ in one important respect from the scheduling of appointments with specific surgeons as named in the referrals: any particular patient may have to see a surgeon other than the one who was recommended by the referring specialist. Similar to the argument that Murray and Berwick developed for the primary care setting (Murray & Berwick, 2003), adopting this appointment system in the surgical services setting would present the patient with a trade-off between the value of consulting with the surgeon recommended by the referring physician and the value of early consultation, which might not be with the surgeon originally recommended.

The purpose of this simulation study was to estimate the impact of methods for scheduling appointments for surgical consultation on the flow of patients from referral to consultation and from consultation to surgery in the context of cardiac surgical services. We compared three appointment systems (assigning patients to a pooled list, to individual lists for specific surgeons, and to the shortest list) in terms of the following performance measures: clearance time for appointment lists (Cottrell, 1980), time to clinic appointment for individual patients (Sobolev et al., 2008) and time to surgery (Sobolev & Kuramoto, 2008). In particular, we were interested in whether the shortest-queue system would reduce the average clearance time, whether it would increase the proportion of patients having appointments each week and whether it would increase the proportion of patients undergoing an operation from wait lists each week. We chose to focus on cardiac surgical care because this type of health care is well structured in terms of the activities involved and is thus amenable to study and improvement (Cohn & Edmunds, 2003).

In this study, we applied the results of a previous study in which we mapped the process of cardiac surgical care at a teaching hospital in British Columbia, Canada, where 650 open-heart surgeries were being performed annually (Sobolev et al., 2006). Three cardiac surgeons had admitting privileges at this hospital and used a shared clinic for outpatient consultations. In this setting, the availability of the surgeons for operations depended on their schedules for consultations, planned operations, on-call duties, and vacations. Sixteen consultation appointments, seven operating room slots for planned operations and eight for urgent cases were available each week; and emergency cases might cause the cancellation of planned operations.

To emphasize the designed nature of this simulation experiment, throughout the paper we have used the terminology suggested by Law, whereby experimental variables are called "experimental factors" and performance variables are called "experimental responses" (Law, 2007). We used performance measures derived from the experimental responses to assess the results of the simulation experiment.

2. Methods

2.1 Modeled activities of surgical care

We simulated the delivery of surgical care using a discrete-event model, which has been described elsewhere (Sobolev et al., 2008). Patient-level models are commonly used to simulate steps in service delivery and response pathways for individual patients (Jun et al., 1999; O'Hagan et al., 2007). Compared with analytical models, simulation models allow the investigator to take into account variations in demand on different weekdays and a realistic schedule for doctors' multiple activities (Elkhuizen et al., 2007). The use of simulations for evaluating health care policy is based on two premises: first, that simulated individual care paths represent the delivery of health services to a patient population and second, that simulation produces care paths that are likely under the policy in question (Sobolev & Kuramoto, 2005). Davies and Davies argued that discrete-event simulation is appropriate when patient entities pass through a series of managerial and clinical activities, and take part in multiple activities (Davies & Davies, 1995). As such, discrete-event models can avoid the unrealistic assumptions of analytical models (Harper & Gamlin, 2003; Sobolev et al., 2008).

In this study, the modeled processes encompassed the continuum of clinical and managerial activities in cardiac surgical care. The diagram in Figure 1 shows activities at preoperative, operative, and postoperative stages included in the simulation model. Table 1 provides further explanation of the modeled activities. Using the Statecharts language, we described the progress of individual patients through surgical care as a series of asynchronous updates in patient records. The updates were produced in response to events generated by parallel finite state machines representing concurrent clinical and managerial activities (Gruer et al., 1998). The Statecharts specifications of these activities were based on the process of cardiac surgical care at a tertiary care hospital in British Columbia, Canada (Vasilakis et al., 2007). The Appendix provides a more detailed description of the simulation approach, its underlying assumptions, and the values of the model parameters.

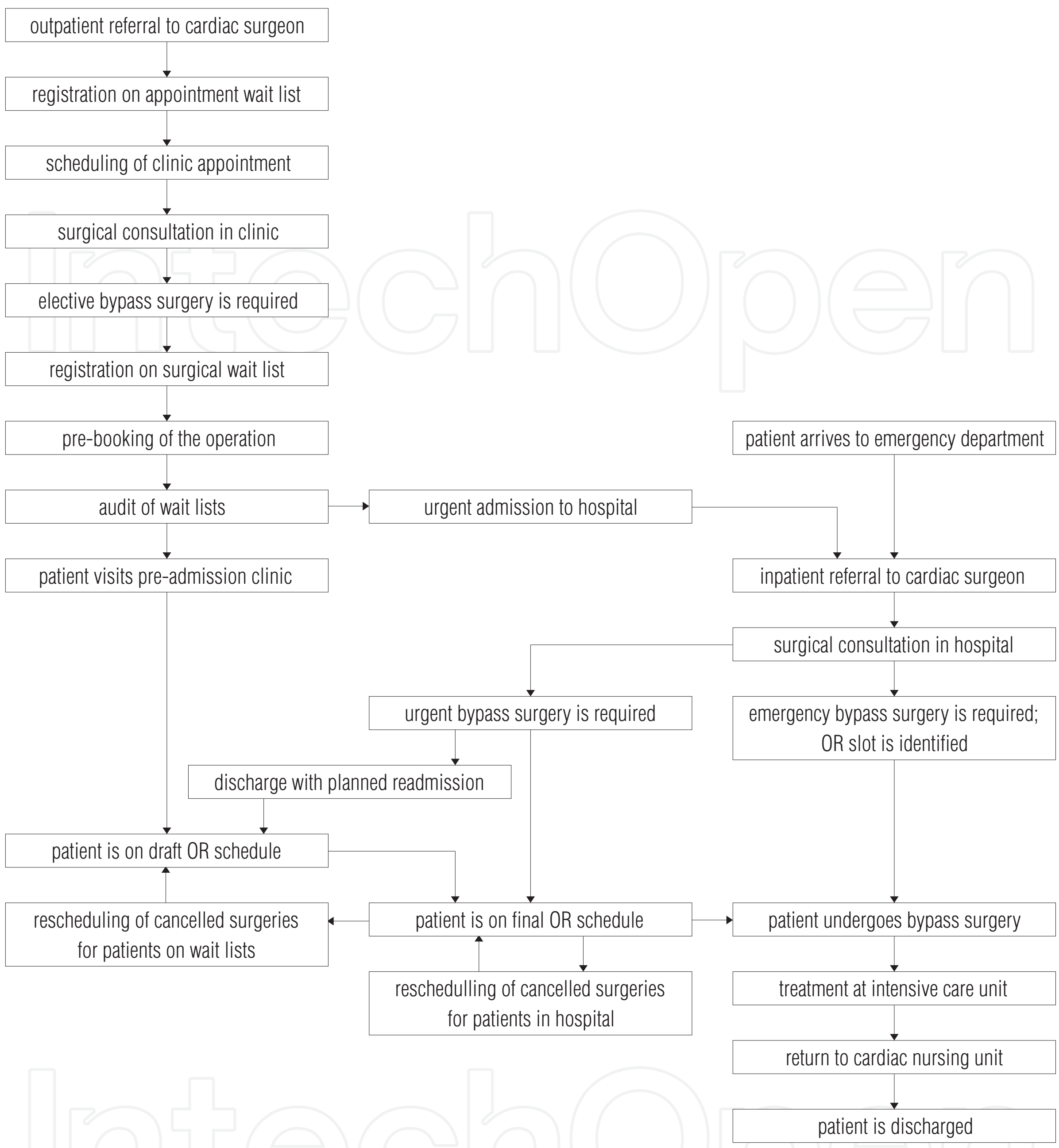


Fig. 1. Flow diagram of clinical and managerial activities included in the simulation model, modified from Sobolev & Kuramoto, 2008 [page 19]

We modeled three care paths that patients with established coronary artery disease are likely to experience, according to initial presentation and subsequent decisions leading to surgery: elective, inpatient, and emergency; these paths have been described in detail elsewhere (Sobolev et al., 2006). The elective path applies to patients for whom surgical consultation and subsequent operation can be safely delayed. The inpatient path applies to patients admitted to hospital from the catheterization laboratory when surgical assessment is urgently needed. The emergency path applies to patients requiring immediate surgical intervention.

Activity	Description
Referral of patients needing elective surgery for outpatient assessment	Patients presenting with symptoms are sent for consultation with surgeon in outpatient clinic
Registration of patients needing elective surgery on appointment list	Sex, age, coronary anatomy, and comorbidity of referred patients are recorded
Scheduling of patients needing elective surgery for consultation appointment	Dates of appointments are determined
Outpatient appointments for elective patients	Surgeon assesses indication for the procedure
Registration of patients needing elective surgery on surgical wait list	Details of patients who require and decide to undergo the operation are recorded
Prebooking of patients needing elective surgery for their operations	Committed dates of surgery within the upcoming 36-week period are determined
Referral of patients requiring urgent surgical consultation	Cardiologist refers patients for after assessment in hospital
In-hospital assessment of patients requiring urgent assessment	On-call surgeon determines patients' suitability for admission to hospital as inpatients
Registration of inpatients in surgical queue	Details are recorded for patients who must undergo the operation and who are admitted directly to hospital
Scheduling of operating time	Inpatients and patients awaiting elective surgery are identified, and hospital resources are reserved
Updating of operating room time	Final schedule for operating room is created
Arrival of emergency patients	Patients requiring emergency operation are sent for procedure
Cancellation of scheduled operations by emergency arrivals	Emergency patients requiring immediate operation replace previously scheduled patients in the operating room schedule
Cancellation of scheduled operations by inpatients	Inpatients requiring surgery replace previously scheduled patients in the operating room schedule
Rescheduling of cancelled procedures	Patients who are still waiting for operation after surgery was canceled are identified, and hospital resources are reserved
Surgical procedures	Operation is performed, during which time patients have access to operating room resources
Recovery in the cardiac surgery intensive care unit (CS-ICU)	Patients recover in the CS-ICU or in another hospital ICU if required
Discharge from hospital	Patients are prepared for postoperative care at home or in rehabilitation or community facilities
Audit of wait lists	Names of patients who die, became inpatients, or are admitted on an emergency basis while waiting for the operation are removed from surgical waiting lists
Unplanned emergency admissions	Patients whose condition deteriorates while waiting for the operation are admitted to hospital as emergency patients or inpatients
Allocation of appointment and theatre slots to surgeons	Appointment and theatre slots are allocated to surgeons according to duty rotation and vacation schedule for upcoming 18-week period

Table 1. Clinical and managerial activities included in the model

In our model, patients referred for consultation with a surgeon were kept on the appointment list with a designated priority (high or low) until an opening for a clinic appointment became available. In the case of individual appointment lists, consultations were scheduled with the surgeon named in the referral. This method ensured that the surgeon chosen by the referring physician assessed each patient. In the case of pooled appointment lists, consultations were scheduled with the first available surgeon (Vasilakis et al., 2007). In the case of the shortest appointment list, patients were placed on the appointment list of the surgeon with the fewest patients waiting. This method maintains an even distribution of patients among surgeons, while giving each surgeon an individual list of specific patients (Edwards et al., 1994).

After the consultation, the office of the consulting surgeon registered on his or her wait list patients who required coronary revascularization, designating the required procedure as high, medium, or low priority according to the affected coronary anatomy and the patient's symptoms. The hospital's booking office assigned patients to the operating room slots that had been allocated to the consulting surgeon according to their priority and date of registration on the wait list. As discussed elsewhere, we considered a situation in which the hospital's booking office prebooked each patient for the next available operating room slot allocated to the consulting surgeon for the upcoming 36-week period (Sobolev et al., 2008). In addition, we allowed patients who were prebooked for surgery to be admitted to the hospital as inpatients or emergency patients if their condition deteriorated before they underwent elective surgery (Sobolev et al., 2003).

A draft schedule for the operating rooms, listing procedures for planned procedures, was generated every Friday. The schedule was finalized the following Monday and could be subsequently changed to reflect the arrival of inpatients and emergency patients, as well as the availability of beds in the intensive care unit (ICU). The latter is an important constraint, because patients recover in the ICU after the operation, and the duration of stay in the ICU may vary among patients.

The availability of the three surgeons for operations and consultations was coordinated through their weekly schedules such that, in any given week, one surgeon was on call (assessing inpatients and performing urgent operations), one performed planned operations, and one conducted outpatient consultations. During weeks in which one surgeon was on vacation, the two remaining surgeons alternated on-call and planned duties, and no consultations were scheduled.

2.2 Experimental design

Rationale for study design

In the evaluation of health care services, there is recognition that hospital-level factors and policies may make the outcomes of patients served in the same hospital relatively similar (Ukoumunne et al., 1999). For the purpose of our study we were concerned that patient-level responses in a given simulation run might be correlated, because scheduling appointments involves complex decision-making at the level of the hospital. To address this concern, we used a cluster randomized design (Donner & Klar, 1994), according to which the simulation runs, rather than the simulated patient entities, were randomly assigned to the three study groups according to appointment system, as described elsewhere (Sobolev & Kuramoto, 2005).

Experimental factors

The experiment consisted of runs of the discrete-event simulation model with different algorithms for scheduling clinic appointments and different combinations of four additional hospital-level experimental factors likely to influence hospital operations: method of allocating operating room slots and the size of the queues for outpatient consultation, elective surgery, and inpatient surgery at the start of the simulation (Table 2). In addition, at entry into the simulation, patient entities were assigned patient-level factors that would influence their progress through the process of care: age, sex, coronary anatomy, comorbidity (i.e., coexisting medical conditions), and priority of elective referral (Davies & Davies, 1995). These patient-level factors were not controlled by the simulation design but rather were assigned randomly according to their frequency in the population of patients undergoing isolated coronary artery bypass surgery.

Experimental responses

Each run generated a group, or cluster, of patients served in a modeled hospital, the cluster size being determined by arrival and service rates and by simulation time. During each run of the simulation, the software recorded output data for the occurrence and timing of simulated events in the patient population, such as referrals, appointments, registrations, cancellations, and the operation itself, as well as unexpected emergency surgery and preoperative death, if such occurred (Table 2). In addition, the simulation records contained the following patient-level experimental responses: time on the appointment list, time on the surgical wait list, priority of registration for operation, and size of the surgical wait list at registration. The experimental response at the hospital level was the number of patients on the appointment list. The full list of output data produced in the simulation experiment is available from the authors on request.

Performance measures

Although ultimately intended to improve patient care, changes in the delivery of hospital care are generally implemented at the hospital level. Management alternatives, however, may be evaluated at either the hospital or the patient level. Hospital-level evaluations are used to compare the performance of hospitals in the study groups. Patient-level evaluations are used to compare the proportions of patients in the study groups with certain outcomes, for example, to determine whether pooling referrals increases the proportion of patients having a consultation each week.

Performance measures in our study were computed from experimental responses generated by the simulation runs. At the hospital level, the performance measure was clearance time for appointment lists, defined as the ratio of the appointment list census to clinic capacity (Cottrell, 1980). As such, the clearance time referred to a hypothetical time within which the list could be cleared if there were no new arrivals. The appointment list census was a count of patients on the appointment list at the end of a 6-week cycle. The clinic capacity was the weekly number of available appointments for that in the cycle. At the patient level, the performance measure was the weekly rate of clinic appointments and the weekly rate of surgery (Sobolev et al., 2008).

Study variables	Possible values
Experimental factors	
Method of scheduling clinic appointment	1 – assignment of patients to individual surgeons' lists
	2 – assignment of patients to one pooled list
	3 – assignment of patients to shortest list
Method of allocating operating room slots	1 – daily split between elective and urgent procedures
	2 – weekly split between elective and urgent procedures
Initial size of queue for outpatient consultation	16, 32, or 48 patients on appointment list
Initial size of queue for elective surgery	21, 28, 35, or 42 patients on surgical wait list
Initial size of queue for inpatient surgery	0, 8, or 16 patients awaiting surgery in hospital cardiac ward
Simulation output data[a]	
Referral date	date
Date of removal from appointment list	date
Reason for removal from appointment list	1 – received appointment
	2 – did not attend
Registration date for surgical list	date
Date of removal from surgical list	date
Reason for removal from surgical list	1 – underwent surgery
	2 – died
	3 – removed for other reason
	4 – cancelled from final operating room list
	5 – unplanned emergency admission
	6 – became inpatient
Experimental responses	
Appointment list census	number of patients on the appointment list at the end of the week
Time on appointment list	number of weeks from referral to removal from appointment list
Time on surgical wait list	number of weeks from registration to removal from surgical wait list
Performance measures	
Hospital clearance time	ratio of appointment list census to clinic capacity (weeks)
Weekly rate of clinic appointments	number of appointments per 100 patient-weeks
Weekly rate of elective surgery	number of procedures per 100 patient-weeks

[a] The full list of output data produced in the simulation experiment is available from the authors on request.

Table 2. Experimental and performance variables

Simulation time

To increase variation in the experimental responses, we simulated hospital operations over six 18-week cycles of allocation of clinic and operating time to three surgeons. In practice, hospitals are evaluated annually, so the performance measures of our experiment could be regarded as representing averages over two years.

Sample-size calculation

We compared performance measures across the three appointment systems such that a difference between two systems could be interpreted as the effect of switching from one system to the other. To determine how many simulation runs would be required we set the sample size to detect the anticipated effects of the appointment systems with high probability. For analyses at the hospital level, we estimated that five runs (i.e., five modeled hospitals) per scheduling method would yield 90% power to detect a one-week difference in the clearance time for clinic appointments in a two-sided 5% significance test (Cohen, 1977).

For analyses at the patient level, dependence between experimental responses in each hospital necessitated adjustment for within-hospital correlation (Sobolev & Kuramoto, 2010). We assumed an average of 3,188 patient-weeks per simulation run and a coefficient of variation of 0.04 (Hayes & Bennett, 1999). We estimated that 5 runs per scheduling method would yield 90% power to detect a 10% difference in the weekly appointment rate between groups of patients in a two-sided 5% significance test (Donner & Klar, 2000).

For the purpose of regression analysis, we increased the number of runs to generate an adequate number of observations per regression variable. Our primary experimental factor was represented by two indicator variables for the three appointment scheduling methods. In addition, two variables represented three initial sizes of the outpatient queue, three variables represented four sizes of the initial queue for elective surgery, two variables represented three sizes of the queue for inpatient surgery, and one indicator variable for method of allocating operating room slots. Therefore, with a total of 10 variables, we estimated that 36 runs per scheduling method were needed, allowing for 10 observations per independent variable (Harrel et al., 1985).

The sample size for assessment of all main effects required 108 runs (36 runs for each scheduling method). This number of runs was less than the 216 runs that would have been required for a full factorial design (Law, 2007). Therefore, we used the Fedorov algorithm (Fedorov, 1972) to ensure an optimal distribution of the experimental factors across the runs. The initial allocation was chosen by randomly selecting design points (individual combinations of the experimental factors) from the full factorial design. The algorithm then switched pairs of design points from the initial design and the remainder of the design space to maximize the determinant of the information matrix for the design output (Atkinson & Donev, 1992).

Coincidently, the number of runs and the number of weeks for evaluation of system performance were the same.

2.3 Statistical analysis

We compared the performance of the scheduling methods at the level of the hospital, with application of linear regression methods to clearance times for appointment lists, and at the level of the patient, with application of discrete-time survival regression methods to waiting times. Linear regression methods model the relation between the average clearance time and experimental factors. Discrete-time survival regression methods model the relation between the time to an event and experimental factors, when many events could occur at the same time (Sobolev et al., 2008). In all of the regression analyses, we used two indicator variables to represent the three methods of scheduling clinic appointments. The reference group (pooled list method) was represented by values of zero for both of the indicator variables.

The coefficients derived from linear regression measured the effects of using the individual list and shortest list methods on the average clearance times for appointment lists, relative to scheduling with pooled lists (Vittinghoff et al., 2007). The average clearance time was estimated as the average of observed clearance times over 18 cycles for each run. The effects of scheduling by the individual list and shortest list methods were compared with an F test (Chatterjee & Hadi, 2006). We used multivariable models to adjust for four experimental hospital-level factors: method of allocating operating room slots and initial size of the queues for outpatient consultations, elective procedures, and inpatient procedures (Table 2).

The odds ratios derived from discrete-time survival regressions measured the effects of using the individual list and shortest list methods on the weekly proportion of patients on the appointment lists who received their appointments and who underwent the operation, relative to what occurred with the pooled list method (Sobolev et al., 2008). In the model for appointment waiting times, we adjusted for the hospital-level factors mentioned above and for five patient-level factors, namely sex, age group, coronary anatomy, comorbidity, and priority of elective referral. In the model for surgical waiting times, we adjusted for the hospital- and patient-level factors, replacing referral priority with priority of registration on the surgical wait list, size of the surgical wait list at registration, and weekly number of inpatient and emergency admissions (Sobolev et al., 2004).

We reported results and constructed tables according to published guidelines for reporting statistics in medicine (Lang & Secic, 2006).

3. Results

3.1 Simulated patients

The 108 simulation runs generated a total of 81,569 referrals for elective procedures, 80,294 urgent cases, and 5,827 emergency cases over six 18-week cycles of allocation of clinic and operating time starting on the arbitrarily chosen day of September 1, 2008. On average, the simulation generated 363 elective referrals, 357 urgent cases, and 26 emergency arrivals per modeled hospital in one year. The modeled surgical services performed 658 procedures per year on average.

3.2 Distribution of hospitals and patients by hospital-level factors

By design, the distribution of simulation runs by hospital-level factors was identical across the three methods of scheduling clinic appointments. More specifically, one-third of the runs were allocated to each of the three levels of initial size of the queue for outpatient consultations, one-quarter to each of the four levels of initial size of the queue for elective procedures, one-third to each of the three levels of initial size of the queue for inpatient procedures, and one-half to each of the two levels of method of allocating operating room slots. As a result, the distribution of outpatient referrals by hospital-level factors was similar across scheduling methods as well.

3.3 Distribution of patients by patient-level factors

The distribution of referrals by patient-level factors was also similar across scheduling methods as shown in Table 3. The majority of referrals were men (about 83%) and about 38% of patients were 60 to 69 years old. Most patients had multivessel disease (about 74%) and either major or minor concurrent conditions (about 50%).

	Scheduling method; no. (%) of referrals		
Characteristic	Individual lists (n=27,268)	Shortest list (n=27,236)	Pooled list (n=27,065)
Age group (years)			
<50	1,901 (7)	1,874 (7)	1,939 (7)
50–59	6,266 (23)	6,148 (23)	6,152 (23)
60–69	10,296 (38)	10,405 (38)	10,133 (37)
70–79	7,953 (29)	7,921 (29)	7,984 (30)
≥80	852 (3)	888 (3)	857 (3)
Sex			
Men	22,574 (83)	22,760 (84)	22,604 (84)
Women	4,694 (17)	4,476 (16)	4,461 (16)
Coronary anatomy			
Left main	4,574 (16)	4,610 (17)	4,472 (16)
Multi-vessel[a]	20,087 (74)	20,049 (74)	19,999 (74)
Limited[b]	2,607 (10)	2,577 (9)	2,594 (10)
Comorbidity			
Major conditions[c]	6,071 (22)	6,109 (22)	5,964 (22)
Other conditions[d]	7,453 (27)	7,355 (27)	7,488 (28)
None	13,744 (51)	13,772 (51)	13,613 (50)
Priority of elective referral			
High	1,892 (7)	1,885 (7)	1,979 (7)
Low	25,376 (93)	25,351 (93)	25,086 (93)

[a] Two- or three-vessel disease with stenosis of the proximal left anterior descending (PLAD) artery
[b] Two-vessel disease with no stenosis of the PLAD artery or one-vessel disease with stenosis of the PLAD artery
[c] Congestive heart failure, diabetes mellitus, chronic obstructive pulmonary disease, rheumatoid arthritis, or cancer
[d] Peripheral vascular disease, cerebrovascular disease, dementia, peptic ulcer disease, hemiplegia, renal disease, or liver disease

Table 3. Simulated referrals for clinic appointments by patient characteristics and scheduling methods

At the time of referral, 93% of the patients had low priority for the consultation. Regardless of the method of scheduling appointments, most of the referred patients had a surgical consultation by the end of the simulation (94% for individual list method, 94% for shortest list method, and 96% for pooled list method). The rest of the patients were still awaiting an appointment because their referral times were close to the end of the simulation period.

At the time of registration on a surgical wait list, about 71% of the cases had medium priority for the operation. The waiting time for elective surgery was 1 week or less for 69% of the patients scheduled through the individual list or the shortest list method; however, the proportion with waiting time of 1 week or less was only 56% for those scheduled via the pooled list method. Of all the patients who were registered on a surgical wait list, 78% underwent the planned procedure. The reasons for removal from the lists without surgery were similar across scheduling methods: 10% of planned procedures were cancelled because no beds were available in the intensive care unit for recovery after surgery and 9% of planned procedures were cancelled because an inpatient was admitted for surgery. Another 3% of patients were removed from the list for other reasons or they remained on the wait list at the end of the simulation (Sobolev & Kuramoto, 2008).

3.4 Clearance times for appointment lists

The average clearance time for appointment lists was similar when patients were scheduled to individual surgeons' lists (5.2 weeks) and when they were assigned to the surgeon with the shortest list (5.3 weeks); however, clearance time was much shorter when a pooled list was used (3.6 weeks) (Table 4). After adjustment for hospital-level factors, the average clearance time was more than 1.5 weeks longer for the individual list or the shortest list method than for the pooled list method (Table 4). There was no difference in clearance times between services using the individual list and shortest list methods (F test statistic = 5.7 for 1 and 97 degrees of freedom, p = 0.26).

Performance measure	**Scheduling method**		
	Individual lists	Shortest list	Pooled list
Hospital level			
Average clearance time (standard deviation), weeks	5.2 (0.7)	5.3 (0.2)	3.6 (0.2)
Difference (95% confidence interval)[a], weeks	1.6 (1.4–1.8)[b]	1.7 (1.5–1.9)[b]	reference group
Patient level			
Appointment rate (95% confidence interval)[c]	19.7 (19.5–20.0)	19.5 (19.3–19.7)	33.9 (33.5–34.3)
Odds ratio (95% confidence interval)[d]	0.22 (0.21–0.22)	0.22 (0.22–0.23)	reference group

[a] Difference relative to the pooled list method, adjusted for initial queue size at clinic appointment, for initial size of queues at registration for elective and urgent surgery, and for method of allocating operating room slots

[b] No difference between individual list and shortest list methods ($p = 0.26$)

[c] Weekly appointment rate was calculated as the number of appointments divided by the sum of wait times (and is expressed per 100 patient-weeks)

[d] Ratio relative to the pooled list method, adjusted for initial queue size at clinic appointment, for initial size of queues at registration for elective and urgent surgery, and for method of allocating operating room slots, and also for age, sex, anatomy, comorbidity, priority at referral, and week from referral

Table 4. Relation between scheduling methods and average clearance times (in weeks), and relation between scheduling methods and weekly rate of clinic appointment

3.5 Weekly rate of clinic appointment

The average weekly number of appointments was similar with the individual list and shortest list methods (about 20 per 100 patients remaining on the appointment list), but was much greater with the pooled list method (about 34 per 100 patients remaining on the list) (Table 4). Patients whose appointments were scheduled by the individual list and shortest list methods had longer waiting times (about one-half had their appointments within 5 weeks) than those scheduled by the pooled list method (about one-half had their appointments within 3 weeks) (Figure 2). After adjustment for hospital-level and patient-level factors, which were described in the Statistical analysis section, the weekly odds that a patient on the wait list would have his or her appointment were 78% lower for both the individual list and shortest list methods relative to the pooled list method (Table 4).

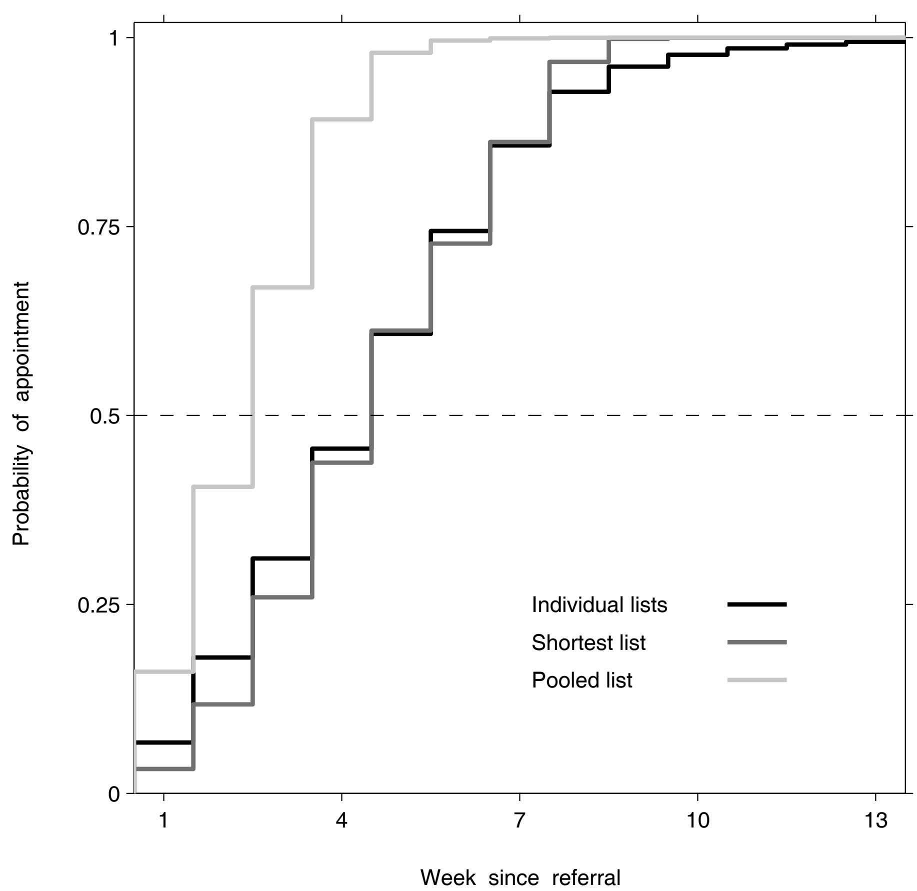


Fig. 2. Estimated probability of patient getting a clinic appointment within a certain waiting time, by scheduling method

3.6 Weekly rate of surgery

Once patients were registered on a surgical wait list, the average weekly number of operations was similar, regardless of the method of scheduling the consultation appointment (34 procedures for every 100 patients remaining on wait lists generated by the individual list and shortest list methods and 32 procedures for every 100 patients remaining on wait lists generated by the pooled list method). The effect of scheduling method on the odds of undergoing an operation was adjusted for a variety of hospital-level and patient-level factors, as described in the Statistical analysis section. After adjustment, and using the pooled list method as the reference group, the weekly odds that a patient on the wait list would undergo the operation were more than 10% with the individual list method (adjusted odds ratio = 1.13, 95% confidence interval 1.10–1.16) and the shortest list method (adjusted odds ratio = 1.12, 95% confidence interval 1.09–1.15). For every eight additional operations (the average weekly number of procedures) that were performed for emergency and urgent inpatient cases, the weekly odds that a patient who was registered on a surgical wait list would undergo the planned operation were reduced by 50% (adjusted odds ratio = 0.50, 95% confidence interval 0.48–0.51).

4. Discussion

We conducted a series of simulation experiments to test for differences between three methods of scheduling clinic appointments in a surgical service. The three methods were placing patients on the appointment list of the surgeon named in the referral (the individual list method), placing patients on the appointment list of the surgeon with the fewest patients waiting (the shortest list method), and placing all patients on one appointment list and scheduling appointments with the first available surgeon (the pooled list method).

We simulated the entire process of surgical care, beginning with the referral and incorporating appointment scheduling, consultation, registration for surgery, pre-surgical assessment, the operation itself, intensive care treatment and discharge from the hospital, accounting for interactions between the appointment and booking systems. Using the Statecharts specifications for the continuum of clinical and managerial activities, a discrete-event simulation model, and a cluster randomized experimental design, for each scheduling method we generated 36 runs, each representing a surgical service with three surgeons who rotated clinic and operating time. The runs differed in terms of the method of allocating slots between urgent and elective procedures and the initial size of queues for outpatient consultation, elective procedures, and inpatient surgery. The delivery of surgical services was simulated over six cycles of allocation of clinic and operating time, to increase variation in the experimental responses.

To estimate the impact of scheduling methods on patient flow, we focused on two common performance measures: clearance time for the appointment list (at the hospital level of analysis) and time to appointment (at the patient level of analysis). Comparisons at the hospital level were used to determine which method of scheduling clinic appointments would reduce the clearance times. Comparisons at the patient level were used to determine which scheduling method would reduce patients' waiting times.

We found that clearance times for appointment lists were more than 1.5 weeks longer for surgical services that used the individual list and shortest list methods than for services that used the pooled list method. After adjustment for hospital and patient factors, the weekly likelihood that patients on an appointment list would have had a consultation with a specialist was 78% lower for services using the individual list and shortest list methods than for those using the pooled list methods. One explanation for these longer clearance times and lower appointment rates can be derived from the observation that in hospitals using the individual list and shortest list methods for scheduling appointments with a specialist, the appointments were scheduled only in time slots assigned to a specific surgeon. If, by chance, the number of patients waiting on an individual appointment list was higher, or the schedule made the surgeon unavailable for appointments during the week following registration on the list, then both the clearance time and the waiting time would be prolonged.

We also observed that the variance in clearance times was similar in services using the pooled list and shortest list methods. It was also substantially smaller as compared with the individual list method. This may be attributed to more predictable patient flow, due to more even distribution of patients among surgeons in the service than was the case for the individual list method. As expected, the scheduling method affected patient flow after the consultation appointment. For example, higher appointment rates for hospitals using the pooled list method resulted in more patients waiting for subsequent care steps, such as surgery. Given that the number of operations done weekly was the same, the weekly rate for elective surgery became higher with scheduling via the individual list and shortest list methods than with scheduling via the pooled list method.

The most important contribution of our simulation study is the assessment of alternative appointment systems that account for interaction between specialists' and hospitals' schedules. Using the Statecharts language, we were able to incorporate the complex pattern of weekly availability of surgeons for operations that depended on their schedules for consultations, planned operations, on-call duties and vacations. We were also able to use information on patient-level factors that influenced the simulated experimental responses, such as referrals, appointments, wait-list registrations, planned and unplanned emergency surgery, cancellations, and preoperative deaths.

We evaluated the appointment systems using specifications for activities that constitute the process of cardiac surgical care. Because these managerial and clinical activities are generic across surgical services, the results of our evaluation may be applicable to other settings where appointments and wait lists are used to manage access to surgical procedures. Indeed, by varying other factors that are likely to influence service performance, such as the method of allocating operating room slots, we were able to delineate the independent effect of methods for scheduling clinic appointments.

However, our model also had several limitations. First, although we were able to account for the availability of surgeons for operations, we lacked information about shortages of other hospital staff, so our model did not consider fluctuations in their availability. A second limitation related to the size of the modeled surgical service. Coordinating clinic and operating room schedules for surgeons might have a different effect in a larger service. Whether the effect of the shortest list system depends on the number of surgeons who share these duties requires further investigation. Third, we did not control the distribution of patient-level factors through the design of experiment but instead assigned these factors randomly according to their frequency in the patient population in British Columbia. The case mix of patients needing elective operations could be different in other regions of the world. For example, women consistently accounted for 20% of patients undergoing isolated coronary artery bypass surgery in the United Kingdom, Norway, France, Italy, and Japan in the period 2000–2005 (Keogh & Kinsman, 2004; Motomura et al., 2008). Conversely, patients who undergo this procedure in the United States are slightly older, with greater proportions of women, diabetic patients, smokers and patients with lung disease. Reasons offered for the lower rates of coronary artery bypass grafting among women include greater comorbidity, which augments the operative risk, and smaller size of the coronary arteries, which presents greater technical challenges and increases the potential for incomplete revascularization (Guru et al., 2004). Determining whether the effect of the appointment system is independent of the case mix requires further investigation.

The results of our simulation experiments may have implications for policies on managing access to elective surgery in a regional network of hospitals. If the size of the appointment list and the weekly number of referrals vary significantly from one hospital to another, policy makers may consider redistributing the cases across surgical services, which would require a centrally managed appointment system. Our findings suggest that compared to other alternatives, pooling referrals will substantially reduce access time for appointment at the expense of a slight delay in the timing of elective operations. However, adopting this appointment system in the surgical services setting would present the patient with the choice of waiting to schedule an appointment with the surgeon named in the referral or seeing another surgeon. Further research is required to explore the impact of patient preferences on the performance of various appointment systems.

5. Appendix

5.1 Simulation approach

We used the Statecharts language to define detailed functional and behavioral specifications of states and transitions within each activity of the delivery of care (Sobolev et al., 2008). This approach allowed us to include realistic features of the processes of scheduling consultations and booking admissions, which made the simulation results applicable to other surgical services.

For example, using Statecharts notions of parallelism and event broadcasting, we represented the availability of surgeons for consultations, scheduled operations and on-call duties by developing one statechart for describing the rotation of duties and vacation schedules and another for describing the allocation of clinic and operating room slots to surgeons according to their weekly availability.

5.2 Underlying assumptions

In constructing the simulation model, we made the following simplifying assumptions.

For each simulation week, the random numbers of referrals for consultations, of emergency patients, and of inpatients were drawn from Poisson distributions, to allow for fluctuations in demand for service.

Patients differed by sex, age group, coronary anatomy, and comorbidity. The distribution of referrals by patient factors was based on historical data obtained from the British Columbia Cardiac Services for the period 1991 through 2000 (Sobolev et al., 2006).

Referred patients could have high or low priority for surgical consultation: patients with high priority were scheduled before those with low priority, and patients with the same priority were scheduled by their respective referral times.

Sixteen consultation appointments were available each week, and all patients attended their appointments.

Seven operating room slots for elective surgery and eight for urgent procedures were available each week. Two methods for allocating operating room slots over weekdays were studied: weekly or daily split between elective and urgent procedures.

Elective cases with high and medium priority were eligible for scheduling in both elective and urgent slots, and those with low priority could be scheduled only in elective slots available to the consulting surgeon.

Emergency and urgent inpatient cases were placed on a current operating room schedule immediately. They were scheduled in urgent slots, if such were available; otherwise, previously scheduled operations could be cancelled to accommodate these cases.

Inpatients whose need for surgery was less urgent were placed on the current schedule if urgent slots were available; otherwise, they were scheduled in available urgent slots the next week.

After surgery, patients recovered in the cardiac surgery intensive care unit (CS-ICU), for an average of one day.

Four beds were available in the CS-ICU. Two additional beds from the main hospital ICU could be used for emergency patients if no CS-ICU beds were available.

If no CS-ICU beds were available for recovery from a planned operation, the operation was cancelled.

When scheduled operations were cancelled, patients with high or medium priority for elective surgery became inpatients, and those with low priority joined a separate queue.

The surgeons' service and vacation schedules were planned according to an 18-week cycle, with a booking horizon of 36 weeks.

The outcomes of decision-making that determined the progress of patients from consultation priority groups to surgical priority groups were governed by binomial (branching) probabilities.

Adverse events, such as deaths or unplanned emergency admissions, that determined whether patients would progress from registration to elective surgery or to removal from the list without surgery were governed by binomial (branching) probabilities. These probabilities were dependent on sex, age, coronary anatomy, and comorbidity.

Table A1 shows the values of the model parameters that were used in all simulation runs, including the number of priority groups, arrival rates, branching probabilities, and surgical capacities.

Priority groups	
Outpatient referral for consultation	high, low
Operation	high, medium, low
Referral rates, patients per week	
High priority for consultation	0.5
Low priority for consultation	6.5
Inpatients	5.8
Emergency	0.5
Probability of progression to next care step	
Patients needing elective surgery, with high consultation priority	
Outpatient assessment to high surgical priority	1
Patients needing elective surgery, with low consultation priority	
Outpatient assessment to medium surgical priority	0.76
Outpatient assessment to low surgical priority	0.24
Inpatients	
Inpatient assessment to inpatient surgical queue	0.5
Inpatient assessment to discharge from hospital	0.5
Probability of leaving intensive care unit, per day	
Elective patients	0.25
Inpatients	0.25
Capacity	
Number of surgeons	3
Weekly number of outpatient consultations	16 (8 on Monday and 8 on Tuesday)
Weekly number of elective slots	7
Weekly number of urgent slots	8
Number of beds for elective patients in cardiac surgery intensive care unit	4
Number of beds for emergency patients in main intensive care unit	2

Table A1. Simulation parameters

6. References

Atkinson, A.C. & Donev, A.N. (1992). Criteria of optimality. In: *Optimum Experimental Designs,* 106-115, Oxford Science Publications

Cayirli, T. & Veral, E. (2003). Outpatient scheduling in health care: A review of literature. *Production & Operations Management*, 12, 4, 519-549, 10591478

Chatterjee, S. & Hadi, A.S. (2006). *Regression Analysis by Example,* Wiley-Interscience, New Jersey

Cohen, J. (1977). Statistical Power Analysis for the Behavioral Sciences, Academic Press, New York

Cohn, L.H. & Edmunds, L.H.J. (2003). *Cardiac Surgery in the Adult,* McGraw-Hill, New York

Cottrell, K.M. (1980). Waiting lists: some problems of definition and a relative measure of waiting time. *Hospital and Health Services Review*, 76, 265-269

Davies, H.T. & Davies, R. (1995). Simulating health systems: modelling problems and software solutions. *European Journal of Operation Research*, 87, 35-44

Donner, A. & Klar, N. (2000). Design and Analysis of Cluster Randomization Trials in Health Research, Arnold Publishing Co., New York

Donner, A. & Klar, N. (1994). Cluster randomization trials in epidemiology: theory and application. *Journal of Statistical Planning and Inference*, 42, 37-56

Edwards, R.H.; Clague, J.E.; Barlow, J.; Clarke, M.; Reed, P.G. & Rada, R. (1994). Operations research survey and computer simulation of waiting times in two medical outpatient clinic structures. *Health Care Analysis*, 2, 164-169

Elkhuizen, S.G.; Das, S.F.; Bakker, P.J. & Hontelez, J.A. (2007). Using computer simulation to reduce access time for outpatient departments. *Quality and Safety in Health Care*, 16, 5, 382-386

Erdem, H.I.; Demirel, T. & Onut, S. (2002). An efficient appointment system design for outpatient clinic using computer simulation. *The Proceedings of the 2002 Summer Computer Simulation Conference,* pp. 299-304.

Fedorov, V.V. (1972). *Theory of Optimal Experiments,* Academic Press, New York

Fone, D.; Hollinghurst, S.; Temple, M.; Round, A.; Lester, N.; Weightman, A.; Roberts, K.; Coyle, E.; Bevan, G. & Palmer, S. (2003). Systematic review of the use and value of computer simulation modelling in population health and health care delivery. *Journal of Public Health and Medicine*, 25, 4, 325-335

Gruer, P.; Koukam, A. & Mazigh, R. (1998). Modelling and quantitative analysis of discrete event systems: a statecharts based approach. *Simulation Practice and Theory*, 6, 397-411

Guru, V.; Fremes, S.E. & Tu, J.V. (2004). Time-related mortality for women after coronary artery bypass graft surgery: a population-based study. *Journal of Thoracic and Cardiovascular Surgery*, 127, 4, 1158-1165

Ham, C.; Kipping, R. & McLeod, H. (2003). Redesigning work processes in health care: lessons from the National Health Service. *Milbank Quarterly*, 81, 3, 415-439

Harper, P.R. & Gamlin, H.M. (2003). Reduced outpatient waiting times with improved appointment scheduling: a simulation modelling approach. *OR Spektrum*, 25, 2, 207-222

Harrel, F.E.; Lee, K.L.; Matchar, D.B. & Reichert, T.A. (1985). Regression models for prognostic prediction: Advantages, problems and suggested solutions. *Cancer Treatment Reports*, 69, 1071-1077

Hayes, R.J. & Bennett, S. (1999). Simple sample size calculation for cluster-randomized trials. *International Journal of Epidemiology*, 28, 319-326

Ho, C.J. & Lau, H.S. (1999). Evaluating the impact of operating conditions on the performance of appointment scheduling rules in service systems. *European Journal of Operational Research*, 112, 3, 542-553, 0377-2217

Jun, J.B.; Jacobson, S.H. & Swisher, J.R. (1999). Application of discrete-event simulation in health care clinics: a survey. *Journal of the Operational Research Society*, 50, 109-123, 0160-5682

Keogh, B. & Kinsman, R. (2004). Fifth national adult cardiac surgical database report 2003: Improving outcomes for patients. Dendrite Clinical Systems, Reading, MA

Klassen, K.J. & Rohleder, T.R. (1996). Scheduling outpatient appointments in a dynamic environment. *Journal of Operations Management*, 14, 2, 83-101, 02726963

Klassen, K.J. & Rohleder, T.R. (2004). Outpatient appointment scheduling with urgent clients in a dynamic, multi-period environment. *International Journal of Service Industry Management*, 15, 167-186, 0956-4233

Lang, T.A. & Secic, M. (2006). *How to report statistics in medicine,* American College of Physicians, Philadelphia

Law, A.M. (2007). *Simulation Modeling & Analysis,* McGraw-Hill, New York

Meredith, P.; Ham, C. & Kipping, R. (1999). Modernising the NHS: booking patients for hospital care. Health Services Management Centre, University of Birmingham, Birmingham

Motomura, N.; Miyata, H.; Tsukihara, H.; Okada, M. & Takamoto, S. (2008). First report on 30-day and operative mortality in risk model of isolated coronary artery bypass grafting in Japan. *Annals of Thoracic Surgery*, 86, 6, 1866-1872

Murray, M. & Berwick, D.M. (2003). Advanced access: reducing waiting and delays in primary care. *Journal of the American Medical Association*, 289, 8, 1035-1040

Naylor, C.D. (1991). A different view of queues in Ontario. *Health Affairs*, 10, 3, 110-128

O'Hagan, A.; Stevenson, M. & Madan, J. (2007). Monte Carlo probabilistic sensitivity analysis for patient level simulation models: Efficient estimation of mean and variance using ANOVA. *Health Economics*, 16, 10, 1009-1023, 1057-9230

Sobolev, B.; Brown, P.; Zelt, D. & Kuramoto, L. (2004). Waiting time in relation to wait-list size at registration: statistical analysis of a waiting-list registry. *Clinical and Investigative Medicine*, 27, 298-305

Sobolev, B.; Harel, D.; Vasilakis, C. & Levy, A.L. (2008). Using the statecharts paradigm for simulation of patient flow in surgical care. *Health Care Manag Sci*, 11, 79-86

Sobolev, B. & Kuramoto, L. (2005). Policy analysis using patient flow simulations: conceptual framework and study design. *Clinical and Investigative Medicine*, 28, 359-363

Sobolev, B. & Kuramoto, L. (2008). Analysis of Waiting-time Data in Health Services Research, Springer, New York

Sobolev, B. & Kuramoto, L. (2010). Cluster-randomized design for simulation-based evaluation of complex healthcare interventions. *Journal of Simulation*, 4, 24-33

Sobolev, B.; Levy, A.; Hayden, R. & Kuramoto, L. (2006). Does wait-list size at registration influence time to surgery? Analysis of a population-based cardiac surgery registry. *Health Services Research*, 41, 23-39

Sobolev, B.; Mercer, D.; Brown, P.; FitzGerald, M.; Jalink, D. & Shaw, R. (2003). Risk of emergency admission while awaiting elective cholecystectomy. *Canadian Medical Association Journal*, 169, 7, 662-665

Sobolev, B.; Sanchez, V.; Kuramoto, L.; Levy, A.; Schechter, M. & FitzGerald, M. (2008). Evaluation of booking systems for elective surgery using simulation experiments. *Healthcare Policy*, 3, 4, 113-124

Ukoumunne, O.C.; Gulliford, M.C.; Chinn, S.; Sterne, J.A.; Burney, P.G. & Donner, A. (1999). Methods in health Service research. Evaluation of health interventions at area and organisation level. *British Medical Journal*, 319, 376-379

Vasilakis, C.; Sobolev, B.; Kuramoto, L. & Levy, A. (2007). A simulation study of scheduling clinic appointments in surgical care: individual surgeon versus pooled lists. *Journal of the Operational Research Society*, 58, 202-211

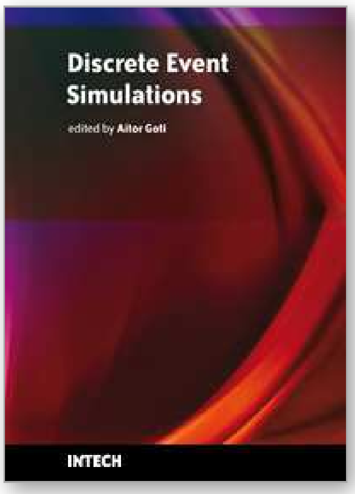
Vissers, J. (1979). Selecting a suitable appointment system in an outpatient setting. *Medical Care*, 17, 1207-1220

Vittinghoff, E.; Glidden, D.V.; Shiboski, S.C. & McCulloch, C.E. (2007). Regression Methods in Biostatistics: Linear, Logistic, Survival, and Repeated Measures Models, Springer, New York

Walshe, K. & Rundall, T. (2001). Evidence-based management: from theory to practice in health care. *Milbank Quarterly*, 79, 3, 429-457

Westeneng, J.B. (2007). Outpatient appointment scheduling: An evaluation of alternative appointment systems to reduce waiting times and underutilization in an ENT outpatient clinic. Dissertation, University of Twente.

Wijewickrama, A. & Takakuwa, S. (2008). Outpatient appointment scheduling in a multi facility system. *Proceedings of the 2008 Winter Simulation Conference,* pp. 1563-1571.



Discrete Event Simulations
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Considered by many authors as a technique for modelling stochastic, dynamic and discretely evolving systems, this technique has gained widespread acceptance among the practitioners who want to represent and improve complex systems. Since DES is a technique applied in incredibly different areas, this book reflects many different points of view about DES, thus, all authors describe how it is understood and applied within their context of work, providing an extensive understanding of what DES is. It can be said that the name of the book itself reflects the plurality that these points of view represent. The book embraces a number of topics covering theory, methods and applications to a wide range of sectors and problem areas that have been categorised into five groups. As well as the previously explained variety of points of view concerning DES, there is one additional thing to remark about this book: its richness when talking about actual data or actual data based analysis. When most academic areas are lacking application cases, roughly the half part of the chapters included in this book deal with actual problems or at least are based on actual data. Thus, the editor firmly believes that this book will be interesting for both beginners and practitioners in the area of DES.